Abstract—We first compare the performance of the diffusion-based molecular communication (DMC) systems employing respectively the on-off keying (OOK), whose demodulation depends on a non-zero threshold, and the binary molecular shift keying (BMSK). Our studies demonstrate that the OOK is hard to operate in practical DMC environments, while the BMSK is more feasible for implementation in practice. Furthermore, the BMSK has the embedded capability to cancel some inter-symbol interference (ISI), making it significantly outperform the OOK in terms of the achievable error performance. Then, we propose a low-complexity ISI cancellation (ISIC) approach for further enhancing the performance of the BMSK. We propose two ways for estimating the parameters involved in the ISIC, both of which are demonstrated highly effective. The performance of the ISIC-assisted BMSK is compared with that of the OOK and that of the BMSK without ISIC, showing that the proposed ISIC approach is capable of significantly improving the error performance of the BMSK.

Index Terms—Molecular communications, diffusion, molecular shift keying, concentration shift keying, inter-symbol interference cancellation.

I. INTRODUCTION

Nano-machines are tiny components that are capable of performing basic computing and sensing tasks [1]. Molecular communication between nano-machines is inspired by the communication mechanisms naturally occurring between living cells, which conveys information between nano-machines with the aid of molecules [2]. In molecular communications, the diffusion-based molecular communications (DMCs) have been recognized as the most practical information transmission method, which relies on the law of diffusion for molecule propagation from transmitters to receivers [3].

The channel modeling in DMCs has been considered in a number of references, such as, in [4–6]. The noise sources and noise statistics in DMCs have firstly been analyzed in [7]. Based on the proposed DMC channel models and DMC noise statistics, data modulation schemes, transceiver design, and performance have widely been investigated. In literature, there are mainly three classes of data modulation schemes for DMCs. The first class relies on the molecule concentration, referred to as the concentration shift keying (CSK) [4–8], which divides the molecule concentration level into $M$ sub-levels so as to convey $\log_2 M$ bits per symbol from a transmitter to its receiver. The second class is the pulse position modulation (PPM) [9], in which information is retrieved from the positions of received molecule concentration pulses. In the above two classes of modulation schemes, one type of molecules is usually used. By contrast, the third class of modulations uses multiple types of molecules, forming the so-called molecule shift keying (MoSK) [2, 10, 11]. Regardless of the class of data modulation employed, DMCs usually experience strong inter-symbol interference (ISI), due to the relatively long delay spread of molecular diffusion propagation in liquid medium. In order to improve the performance of DMCs, a range of advanced detection algorithms have been proposed [12–15], which include the sequence detectors in the principles of maximum a-posteriori (MAP) and maximum likelihood (ML) [12–15], linear equalizer in the principles of minimum mean-square error (MMSE) [13], and the decision-feedback equalizer (DFE) [13].

However, the advanced detection algorithms as mentioned above are too complicated to be implemented at nano-scale devices in the foreseeable future. Furthermore, considering the development of nowadays nano-technologies, the implementation of a multi-level modulation scheme, such as the $M$-level CSK and $M$-level MoSK, relying on low-complexity detection is also highly challenging, when the number of modulation levels is relatively high. Additionally, although in literature various data modulation strategies with optimum detection have been considered in the context of DMCs, as reviewed above, the impact of practical DMC environments on the optimality of detection has rarely been investigated. For example, considering the $M$-level CSK of depending on $(M - 1)$ thresholds in detection, it is in fact very hard to set these thresholds to their near-optimum values in practice, as they are dependent on many factors, including transmission distance, data rate, stationarity of transmitter, medium’s diffusion coefficients, method used by receiver to measure molecule concentration, etc. Furthermore, in DMCs, channel noise is non-stationary and signal dependent. Therefore, at least in the short-term, it is critical for DMCs to employ the low-complexity modems, which are also robust to operate in DMC channels.

Against the above-concerned issues, specifically, in this paper, we first investigate and compare two data modulation schemes, namely the binary CSK, which we call the on-off keying (OOK), and the binary MoSK, which we name as the BMSK, both of which have the lowest complexity for implementation under ideal conditions. Our studies demonstrate that the performance of the OOK is sensitive to the threshold used in detection, the optimum value of which is seems very hard to achieve in practical DMC environments. By contrast, when two types of molecules with similar diffusion coefficients are employed, the BMSK is highly flexible and robust for operation. Furthermore, in comparison to the OOK, the BMSK has an embedded property that the ISI induced by the two types of molecules cancels each other, making its error performance significantly outperform that of the OOK. In order to further improve the performance of the BMSK, we then propose a low-complexity ISI cancellation (ISIC) approach from improving the one proposed in [14]. Our studies demonstrate that the proposed approach is capable of efficiently mitigating the ISI, so that the BMSK is able to support a higher data rate for a required error rate.

The rest of the paper is organized as follows. In section II, we describe the DMC system model and state the main assumptions. Section III provides the principles of the DMCs employing OOK modulation, while Section IV copes with the principles of the BMSK. In Section V, the proposed ISIC approach is detailed. Section VI demonstrates the performance results and provides some analysis and discussion, and finally, in Section VII, we summaries the main conclusions.

II. SYSTEM MODELING AND ASSUMPTIONS

We consider a DMC system, which consists of a transmitter, a molecular diffusion channel and a receiver. At the transmitter, information is encoded into the molecular release patterns, which are propagated over the molecular diffusion channel. At the receiver, information is recovered according to the time-varying concentration caused by the molecules emitted by the transmitter. To abstract and simplify the communication system model, some typical assumptions in references, e.g., [16], are applied. Specifically, the transmitter is treated as a point molecule source, whose released molecules do not
interact with the transmitter as well as with the liquid propagation medium. The receiver is assumed to be able to ideally measure the molecule concentration within a spherical detection range with a radius of $\rho$. We assume that the positions of both transmitter and receiver are fixed during a transmission. Furthermore, we assume that molecules at transmitter are released as an impulse function. Then, according to the Fick’s law of diffusion [16], the molecular concentration at a given position with a distance $r$ from the transmitter can be described as

$$c(t) = \frac{Q}{(4\pi D t)^{3/2}} \exp \left( -\frac{r^2}{4Dt} \right)$$  \hspace{1cm} (1)

where $D$ is the diffusion coefficient of the medium, $t$ is the propagation time, and $Q$ is the number of molecules emitted by the transmitter at $t = 0$.

As shown in Fig. 1, when an impulse of molecules is released at $t = 0$, the concentration at the receiver reaches its maximum at the instant of $t_d$ dependent on $r$ as [16]

$$t_d = \frac{r^2}{6D}$$  \hspace{1cm} (2)

When substituting (2) into (1), we can find that the peak value of $c(t)$ is

$$c_{\text{max}} = \left( \frac{3}{2\pi e} \right)^{3/2} \frac{Q}{r^3},$$  \hspace{1cm} (3)

showing that the peak value of received pulses decays with $r^3$.

III. ON-OFF KEYING MODULATION AND DEMODULATION

In this section, we review the principles of the OOK for DMCs, which is a typical molecular modulation considered in many references, such as, [11, 13–16]. When the OOK is used to encode a binary information sequence expressed as $\{b_j\} = \{b_0, b_1, \ldots, b_j, \ldots\}$, the transmitter emits an impulse of molecules, when it sends $b_j = 1$, while releases no molecules, when it sends $b_j = 0$. Correspondingly, the noiseless molecule concentration measured by the receiver within its detection space can be expressed as

$$y(t) = \sum_{j=0}^{J} b_j c(t - jT)$$  \hspace{1cm} (4)

where $T$ represents the symbol duration, determining an information rate of $R = 1/T$ bits per second, and $J = \lfloor t/T \rfloor$ is an integer, representing the number of bits transmitted within $[0, t)$.

When noise is taken into account, the total molecular concentration observed at the receiving space can be formulated as [16]

$$z(t) = \sum_{j=0}^{J} b_j c(t - jT) + n(t)$$  \hspace{1cm} (5)

where $n(t)$ is the particle counting noise caused by a random process. According to references [14], this noise can be approximated as the Gaussian noise with zero mean and a variance of $\frac{n(t)}{V_R}$, i.e.,

$$n(t) \sim N\left(0, \frac{n(t)}{V_R}\right),$$

where $V_R = \frac{4}{3} \pi \rho^3$ is the volume of the spherical detection space. Explicitly, the noise variance is dependent on the molecule concentration of (4) at the receiver, and it is non-stationary.

As shown in Fig. 1, when an impulse of molecules is sent at $t = 0$, it would be desirable for the receiver to sample for the molecule concentration at $t = t_d$, in order to attain the most reliable detection. Therefore, in order to detect the $u$th bit, we assume that the receiver samples for the molecule concentration at $t = uT + \hat{t}_d$, where $\hat{t}_d$ represents the estimate to $t_d$. This gives the decision variable for the $u$th bit as

$$Z_u = z(t = uT + \hat{t}_d) = \sum_{j=0}^{u} b_j c([u - j]T + \hat{t}_d) + n(uT + \hat{t}_d), \hspace{1cm} u = 0, 1, \ldots$$  \hspace{1cm} (6)

Let us define $c_{u-j} = c([u - j]T + \hat{t}_d)$ and $n_u = n(uT + \hat{t}_d)$. Then, the above equation can be written as

$$Z_u = \sum_{j=0}^{u} b_j c_{u-j} + n_u, \hspace{0.5cm} u = 0, 1, \ldots$$  \hspace{1cm} (7)

Explicitly, the detection of bit $u$ experiences the ISI imposed by the bits sent before bit $u$. Let us assume that the length of the ISI is $I$ bits. Then, when applying the variable transform of $i = u - j$, we can express $Z_u$ in (7) in the form of

$$Z_u = \sum_{j=\max\{0,u-I\}}^{u} b_j c_i + n_u, \hspace{1cm} u = 0, 1, \ldots$$  \hspace{1cm} (8)

Considering that $n(t)$ is approximated as the Gaussian distribution, the probability density function (pdf) of $Z_u$ can be derived from (8), which can be expressed as [14]

$$Z_u \sim N(\mu_u, \sigma_u^2)$$  \hspace{1cm} (9)

where the mean and variance are given by

$$\mu_u = \sum_{i=0}^{\min\{I,u\}} b_{u-i} c_i; \hspace{1cm} \sigma_u^2 = \frac{1}{V_R} \sum_{i=0}^{\min\{I,u\}} b_{u-i} c_i$$  \hspace{1cm} (10)

Note that, the PDF of the noise samples $\{n_u\}$ is given by $n_u \sim N(0, \sigma_n^2)$.

In order to recover the received information conveyed by the OOK modulation, let us assume that the receiver uses a threshold of $C_T$ for decision making. Considering that the concentration presenting at the receiver has the function as shown in Fig. 1, it is convenient to set the threshold relative to the peak $c_{\text{max}}$ as

$$C_T = \alpha c_{\text{max}}$$  \hspace{1cm} (11)
where $0 \leq \alpha \leq 1$ can be referred to as the normalized threshold. Consequently, by comparing the corresponding observation with the threshold, the receiver can make the decision of a bit as

$$
\hat{b}_u = \begin{cases} 
1, & \text{when } Z_u \geq C_T \\
0, & \text{when } Z_u < C_T
\end{cases}, \quad u = 0, 1, \ldots
$$

(12)

It is well known that the OOK in principle has the advantage of low-complexity detection. However, in the OOK modulation, it is usually very hard to set a near-optimum threshold in detection, as the optimum threshold is dependent on and also sensitive to both the channel and the signal-to-noise ratio (SNR). The situation becomes even worse in DMCs. First, as shown in (1), the concentration presenting at the receiver is a function of both the distance of the receiver from the transmitter, and of the time of the receiver sampling the channel. Second, as shown in (8), strong ISI exists in the detection. Furthermore, as shown in (10), the noise power is not a fixed value, but is dependent on the real-time binary sequence sent by the transmitter, which makes the noise not stationary. From these factors, we may be implied that in practical DMCs, a near-optimum threshold for detection might be hard to find and also hard to maintain. As our simulation results in Section VI show, the error performance of the OOK is very sensitive to the symbol duration $T$ and the SNR, as defined later in Section VI.

IV. BINARY MOLECULE SHIFT KEYING MODULATION AND DEMODULATION

In order to circumvent the threshold setting problem experienced by the OOK, the BMSK modulation can be employed. Furthermore, as our analysis below shows, the BMSK in DMCs naturally employs the capability to mitigate ISI. Consequently, it outperforms the OOK in terms of the error performance, as demonstrated by our simulation results in Section VI. Let us below describe in detail the principles of the BMSK.

When the BMSK is employed by DMCs, we assume that the transmitter employs two types of molecules, namely Type-A and Type-B, which are preferred to having a similar diffusion coefficient in a considered propagation medium. Again, the binary sequence to be transmitted be $\{b_j\} = \{b_0, b_1, \ldots, b_j, \ldots\}$. Then, under the BMSK, the transmitter emits an impulse of Type-A molecules, when $b_j = 1$, while releases an impulse of Type-B molecules, when it sends $b_j = 0$. Then, following the analysis in Section III, the decision variable for $b_u$ can be formed as

$$
Z_u = \sum_{i=0}^{\min{\{I,u\}}} b_{u-i} c_{A,i} - \sum_{i=0}^{\min{\{I,u\}}} (1 - b_{u-i}) c_{B,i} + n_u,
$$

where $\{c_{A,i}\}$ and $\{c_{B,i}\}$ are respectively the samples of the concentration of Type-A and Type-B molecules, obtained from sampling $c_A(t)$ and $c_B(t)$ at the time of $t = iT + \hat{t}_d$ with $i = 0, 1, \ldots$. Let us assume that the concentration functions of $c_A(t)$ and $c_B(t)$ have the same shape. Then, based on (13), the decision is made according to the rules of

$$
\hat{b}_u = \begin{cases} 
1, & \text{when } Z_u \geq C_T \\
0, & \text{when } Z_u < C_T
\end{cases}, \quad u = 0, 1, \ldots
$$

(14)

As seen in (14), the decision boundary is a fixed value of 0.

Furthermore, (14) can be expressed as

$$
Z_u = b_{u-1} c_{A,0} - (1 - b_{u-1}) c_{B,0} + \sum_{i=1}^{\min{\{I,u\}}} b_{u-i} c_{A,i} - \sum_{i=1}^{\min{\{I,u\}}} (1 - b_{u-i}) c_{B,i} + n_u,
$$

(15)

which explicitly shows the ISI terms. Since both $\sum_{i=1}^{\min{\{I,u\}}} b_{u-i} c_{A,i}$ and $\sum_{i=1}^{\min{\{I,u\}}} (1 - b_{u-i}) c_{B,i}$ are always positive values, they will cancel each other after the subtraction operation. Furthermore, we can be implied that the effect of ISI mitigation enhances, when 0’s and 1’s are evenly distributed in the transmitted binary sequence. Therefore, the BMSK embeds certain capability to mitigate ISI. However, when 0’s and 1’s are not evenly distributed, the ISI in the BMSK-assisted DMCs can be still severe. Therefore, in the coming section, we address the ISIC by first improving the ISIC in the OOK-assisted DMCs, followed by extending the ISIC approach to the BMSK-assisted DMCs.

V. INTER-SYMBOL INTERFERENCE CANCELLATION

In (14), a very simple but highly effective ISIC method has been proposed, when the DMCs with OOK is considered. In this method, instead of using the decision variables of (6), the decision variables are generated as

$$
Z_u = z(t = uT + \hat{t}_d) - z(t = uT)
$$

(16)

$$
= \sum_{j=0}^{u} b_j c([u - j]T + \hat{t}_d) + n(uT + \hat{t}_d)
$$

$$
- \left( \sum_{j=0}^{u} b_j c([u - j]T) + n(uT) \right)
$$

(17)

As shown in (16), the decision variable is formed by the difference between two observations, $z(t = uT + \hat{t}_d)$ and $z(t = uT)$, of the molecule concentration obtained at the receiver. With referring to Fig. 1, we can know that the first observation obtained by sampling $z(t)$ of (5) at $t = uT + \hat{t}_d$ motivates to measure the molecule concentration peak after sending the $u$th bit $b_u$. By contrast, the second observation is obtained by sampling $z(t)$ at $t = uT$, i.e., at the start of sending the $u$th bit $b_u$, which is used as the estimate of the ISI imposed on the $u$th bit $b_u$ at $t = uT + \hat{t}_d$. Therefore, after the subtraction operation seen in (16), most of the ISI will be canceled, especially, in the case that the transmission rate $R = 1/T$ is relatively low, resulting in that the ISI at $t = uT$ is similar as that at $t = uT + \hat{t}_d$.

However, when the transmission rate becomes high, the ISI obtained at $t = uT$ may be very different from that at $t = uT + \hat{t}_d$. This becomes severer, when $b_{u-1} = +1$ was sent before $b_u$. Let us refer to Fig. 1 and assume that the transmission rate is high, resulting in that the symbol duration $T$ is only slightly larger than $\hat{t}_d$. In this case, we can be implied that the ISI at $t = uT$ can be much larger than the ISI at $t = uT + \hat{t}_d$ due to the fast decrease of the molecule concentration resulted from the most recent transmissions. Consequently, the ISIC in (16) results in over-cancellation. In order to improve the performance of ISIC, therefore, we propose a modified ISIC scheme, which forms the decision variables according to the formula of

$$
Z_u = z(t = uT + \hat{t}_d) - \lambda_u z(t = uT)
$$

(18)

where $0 \leq \lambda_u \leq 1$ is used to scale the ISI measured at $t = uT$, so that the best ISIC effect at $t = uT + \hat{t}_d$ is attained. For convenience, it is referred to as the ISIC scaling factor.

In practice, the near-optimum value of $\lambda_u$ for given transmission rate and pulse shape may be found via simulations. Furthermore, we
may use the following approach to estimate a value for $\lambda_u$. Let us assume for simplicity that the system is operated in its steady state, meaning that $u >> 0$. Let us use $L$ ISI symbols to estimate $\lambda_u$. Then, we can calculate $L$ coefficients as follows:

$$
\beta_{u-1} = \frac{c(T + \hat{\lambda}_d)}{c(T)}
$$

$$
\beta_{u-2} = \frac{c(2T + \hat{\lambda}_d)}{c(2T)}
$$

... 

$$
\beta_{u-L} = \frac{c(LT + \hat{\lambda}_d)}{c(LT)}
$$

which can be calculated, once the pulse $c(t)$ presenting at receiver is known. Let the estimates of these $L$ ISI symbols be expressed as $\hat{b}_{u-L}, \ldots, \hat{b}_{u-1}$. At moment, we assume that these symbols are correctly detected. Then, we can build the relationship of

$$
\hat{\lambda}_u \times \sum_{j=1}^{L} \hat{b}_{u-j} c(jT) = \sum_{j=1}^{L} \hat{b}_{u-j} \beta_{u-j} c(jT)
$$

where the left-hand side is the ISI at $t = uT$ scaled by $\hat{\lambda}_u$, while the right-hand side is the ISI at $t = T + \hat{\lambda}_d$ obtained by applying the relationships in (19), both are generated by the $L$ ISI symbols considered. Finally, from (20) we can obtain an estimate to $\lambda_u$ as

$$
\hat{\lambda}_u = \sum_{j=1}^{L} \hat{b}_{u-j} \beta_{u-j} c(jT) / \sum_{j=1}^{L} \hat{b}_{u-j} c(jT)
$$

Above the value of $\hat{\lambda}_u$ is estimated by assuming that all the $L$ ISI symbols are correctly detected. In practice, error detection always occurs. Equation (21) indicates that, if an error detection occurs, it will affect the detection of its following $L$ symbols. However, in the proposed ISIC scheme, the effect of erroneous detection is limited. This is because $\hat{\lambda}_u$ is a ratio, an erroneous symbol only results in that $\hat{\lambda}_u$ becomes slightly larger or smaller, but in any of these cases, it satisfies $0 < \hat{\lambda}_u \leq 1$. Hence, it only results in slightly over-cancellation or slightly under-cancellation of the ISI, but not severely degrades the performance, as demonstrated by our simulation results in Section VI.

The above ISIC scheme can be readily extended to the BMSK-assisted DMCs. In this case, the decision variables can be formed as

$$
Z_u = \left[ z_A(t = uT + \hat{\lambda}_d) - \lambda_{A,u} z_A(t = uT) \right]
- \left[ z_B(t = uT + \hat{\lambda}_d) - \lambda_{B,u} z_B(t = uT) \right]
$$

where $0 \leq \lambda_{A,u}, \lambda_{B,u} \leq 1$. In (22), $\lambda_{A,u}$ can be estimated in the same way as shown in (21) after using $c_A(t)$ to replace $c(t)$, while $\lambda_{B,u}$ can be estimated as

$$
\hat{\lambda}_{B,u} = \sum_{j=1}^{L} (1 - \hat{b}_{u-j}) \beta_{u-j} c_B(jT) / \sum_{j=1}^{L} (1 - \hat{b}_{u-j}) c_B(jT)
$$

Let us now provide some performance results obtained from Monte-Carlo simulations to demonstrate the achievable performance of the DMC systems employing the OOK, BMSK, as well as the ISIC-enhanced BMSK.

VI. PERFORMANCE RESULTS

In this section, we demonstrate the error performance of the DMCs employing the OOK, BMSK or the ISIC-assisted BMSK, as well as compare their performance. The error performance is depicted with respect to the SNR, which is defined as the ratio between the power received from a single impulse of molecules and the noise power, given by

$$
\text{SNR} = \frac{\beta_0^2}{\mathbb{E}[\sigma_0^2]} = \frac{\beta_0^2}{\sqrt{\text{C}}^2} = \text{SNR}_{C}
$$

From (24) and the analysis in Section II, we can know that, when given $D$ and $r$ in (1), the SNR is only dependent on the number of molecules $Q$ emitted by one pulse and the volume $V_R$ used for density measurement. In our simulations, we set $D = 2.2 \times 10^{-9}$ m$^2$/s(ether/s) and the radius of the spherical detection space to $\rho = 1$ nano meter (nm). Furthermore, the length $I$ of the ISI is determined by the equation of

$$
I \triangleq \text{arg}_{\beta} \left\{ \beta_0 \leq 0.1\% \right\}
$$

First, let us demonstrate the impact of the detection threshold on the bit-error-rate (BER) performance of the DMC systems employing the OOK in Figs.2 and 3. Specifically, Fig. 2 shows the BER versus normalized threshold $\alpha$ with respect to different SNR, while Fig. 3 depicts the BER versus normalized threshold with respect to different
Fig. 4. Comparison of BER versus SNR performance of the OOK with optimal threshold and the BMSK, with respect to different symbol intervals of $T$.

Fig. 5. Comparison of BER versus SNR performance of the OOK with non-optimal threshold and the BMSK, in terms of different symbol intervals of $T$.

symbol interval $T$. Explicitly, both figures demonstrate that the BER performance of OOK is highly dependent on the threshold applied in detection. The achievable BER performance of OOK is very sensitive to the threshold, and applying a mis-matched threshold significantly degrades the achievable performance. In addition to the above, as seen in Fig. 2, the optimum threshold slightly increases as the SNR increases, and the BER performance becomes more sensitive to the threshold as the SNR increases. By contrast, as shown in 3, the symbol interval or the information rate has an apparent effect on the threshold setting. When the symbol interval reduces or when the information rate increases, the optimum threshold increases significantly, and the BER performance achieved at the optimum thresholds degrades. This is the result of the ISI increase due to the reduced symbol interval. In summary, the achievable performance of the OOK-assisted DMC systems is highly dependent on the threshold applied in detection, and the optimum threshold is very sensitive to the communications environments as well as the information rate. These facts make the OOK hard to operate in practice and also hard to attain its expected near-optimum performance, even though it is in principle simple for operation.

Fig. 6. BER versus the ISIC scaling factor $\lambda$, as seen in (22), for the BMSK-assisted DMCs with communication distance $r = 350$ nm or 450 nm.

In Figs. 4 and 5, we compare the BER versus SNR performance of the OOK with that of the BMSK, when different symbol intervals are assumed. In Fig. 4, the optimal threshold is employed by the OOK, while in Fig. 5, we assume the non-ideal threshold applied. In the case that the threshold is non-ideal, we assume that it obeys the Gaussian distribution with its mean given by the optimum threshold, and a variance of $0.01$, i.e.,

$$\alpha \sim \mathcal{N}(\alpha_{\text{optimal}}, 0.01)$$  \hspace{1cm} (26)

From Figs. 4 and 5, we observe that the BER performance of the BMSK is always better than that of the OOK. Typically, even when the optimum threshold is employed by the OOK, as seen in Fig. 4, the BMSK is at least 2 dB better than the OOK, provided that the BER is lower than $10^{-2}$. By contrast, when non-ideal threshold is employed by the OOK, as shown in Fig. 5, the BMSK outperforms the OOK by about 3 dB, when the BER is in the range below $10^{-3}$. Additionally, from these figures, we are implied that the performance loss of the OOK is about 1 dB, even when the threshold has only very small random changes (reflected by the variance of 0.01) around the optimum threshold.

In Fig. 6, we compare the BER performance of the BMSK, and the BMSK with the ISIC supported by the optimum $\lambda$ values obtained via simulations (BMSK(O)) and that supported by the $\lambda$ values evaluated from (21) and (23) (BMSK(F)). As shown in the figure, when communicating at a high data rate (corresponding to $T = 3 \times 10^{-5}$ s), using ISIC is able to significantly improve the performance, provided that the SNR is sufficiently high. However, when the communication rate is relatively low (corresponding to $T = 5 \times 10^{-5}$ s), applying ISIC
For all the schemes considered, the BER performance becomes worse as the transmission distance increases, as the result of increased ISI at given $T$. Over all the transmission ranges considered, the BMSK significantly outperforms the OOK, while the ISIC brings a big gain to the BMSK. Again, the performance achieved by applying the ISIC scaling factors obtained from formulas is near-optimum.

VII. CONCLUSIONS

In this paper, we have studied the error performance of the DMCs employing OOK or BMSK, with the emphasis on their operational concerns in practical DMC environments. Our studies explain that the OOK scheme is highly sensitive to the environment changes, and hence difficult to manage in practice, while the BMSK is feasible for practical implementation. Then, we have proposed an ISIC approach and studied its effectiveness with the BMSK. We have considered different approaches for estimating the ISIC scaling factors for operation in the ISIC. Our performance results demonstrate that applying the ISIC can significantly improve the error performance of the BMSK, especially, when the SNR is relatively high.

REFERENCES


